Lecture 2 – MapReduce: Theory and Implementation

CSE 490H

Annoucements

- Assignment 1 available super-soon (will post on mailing list)
- Start by reading version already on the web
  - “How to connect/configure” will change
  - The “meat” of the assignment is ready

Brief Poll Questions

- Has everyone received an email on the mailing list yet?
- What OS do you develop in?
- Do you plan on using the undergrad lab?

Two Major Sections

- Lisp/ML map/fold review
- MapReduce

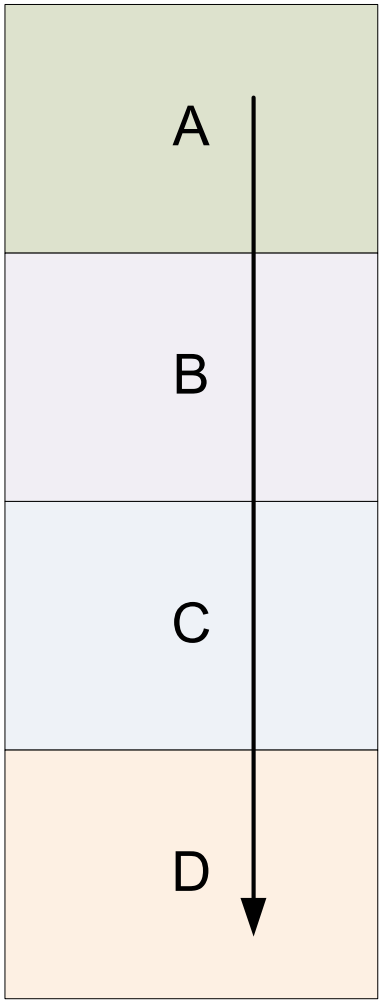
Making Distributed Systems Easier

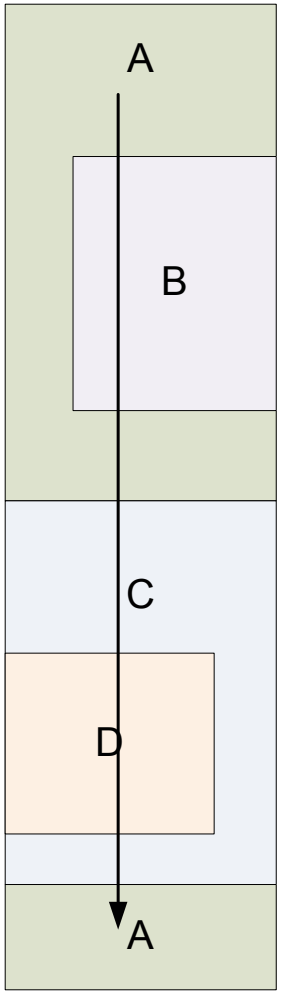
What do you think will be trickier in a distributed setting?

Making Distributed Systems Easier

- Lazy convergence / eventual consistency
- Idempotence
- Straightforward partial restart
- Process isolation

Functional Programming Improves Modularity





Functional Programming Review

- Functional operations do not modify data structures: They always create new ones
- Original data still exists in unmodified form
- Data flows are implicit in program design
- Order of operations does not matter

Functional Programming Review

```
fun foo(l: int list) =
  sum(l) + mul(l) + length(l)
```

Order of sum() and mul(), etc does not matter – they do not modify *l*

“Updates” Don’t Modify Structures

```
fun append(x, lst) =
  let lst' = reverse lst in
    reverse ( x :: lst' )
```

The append() function above reverses a list, adds a new element to the front, and returns all of that, reversed, which appends an item.

But it *never modifies lst*!

Functions Can Be Used As Arguments

```
fun DoDouble(f, x) = f (f x)
```

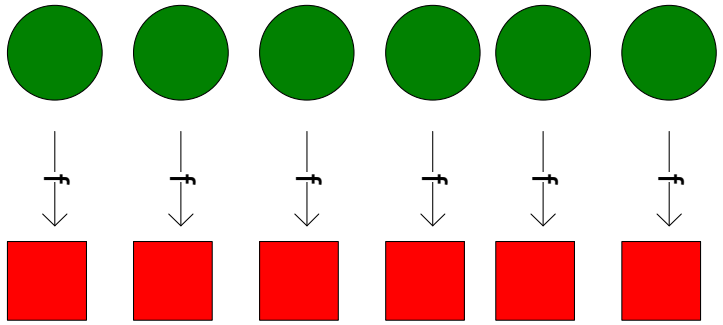
It does not matter what f does to its argument; DoDouble() will do it twice.

What is the type of this function?

Map

map f lst: (’a->’b) -> (’a list) -> (’b list)

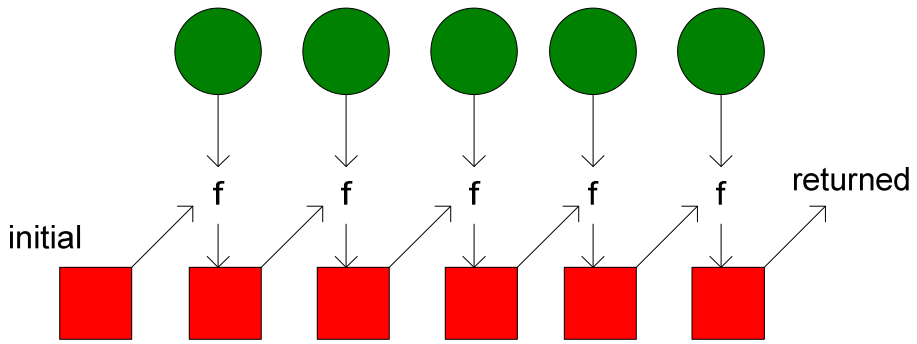
Creates a new list by applying f to each element of the input list; returns output in order.



Fold

fold f x_0 lst: ('a*'b->'b)->'b->('a list)->'b

Moves across a list, applying *f* to each element plus an *accumulator*. f returns the next accumulator value, which is combined with the next element of the list



fold left vs. fold right

- Order of list elements can be significant
- Fold left moves left-to-right across the list
- Fold right moves from right-to-left

SML Implementation:

```
fun foldl f a []       = a
  | foldl f a (x::xs) = foldl f (f(x, a)) xs

fun foldr f a []       = a
  | foldr f a (x::xs) = f(x, (foldr f a xs))
```

Example

```
fun foo(l: int list) =
  sum(l) + mul(l) + length(l)
```

How can we implement this?

Example (Solved)

```
fun foo(l: int list) =
  sum(l) + mul(l) + length(l)

fun sum(lst) = foldl (fn (x,a)=>x+a) 0 lst
fun mul(lst) = foldl (fn (x,a)=>x*a) 1 lst
fun length(lst) = foldl (fn (x,a)=>1+a) 0 lst
```

A More Complicated Fold Problem

- Given a list of numbers, how can we generate a list of partial sums?

e.g.: [1, 4, 8, 3, 7, 9] →

[0, 1, 5, 13, 16, 23, 32]

A More Complicated Map Problem

- Given a list of words, can we: reverse the letters in each word, and reverse the whole list, so it all comes out backwards?

[“my”, “happy”, “cat”] -> [“tac”, “yppah”, “ym”]

map Implementation

```
fun map f []        = []
  | map f (x::xs) = (f x) :: (map f xs)
```

- This implementation moves left-to-right across the list, mapping elements one at a time
- … But does it need to?

Implicit Parallelism In map

- In a purely functional setting, elements of a list being computed by map cannot see the effects of the computations on other elements
- If order of application of *f* to elements in list is *commutative*, we can reorder or parallelize execution
- This is the “secret” that MapReduce exploits

MapReduce

Motivation: Large Scale Data Processing

- Want to process lots of data (> 1 TB)
- Want to parallelize across hundreds/thousands of CPUs
- … Want to make this easy

MapReduce

- Automatic parallelization & distribution
- Fault-tolerant
- Provides status and monitoring tools
- Clean abstraction for programmers

Programming Model

- Borrows from functional programming
- Users implement interface of two functions:

  - `map (in_key, in_value) ->`
    `(out_key, intermediate_value) list`

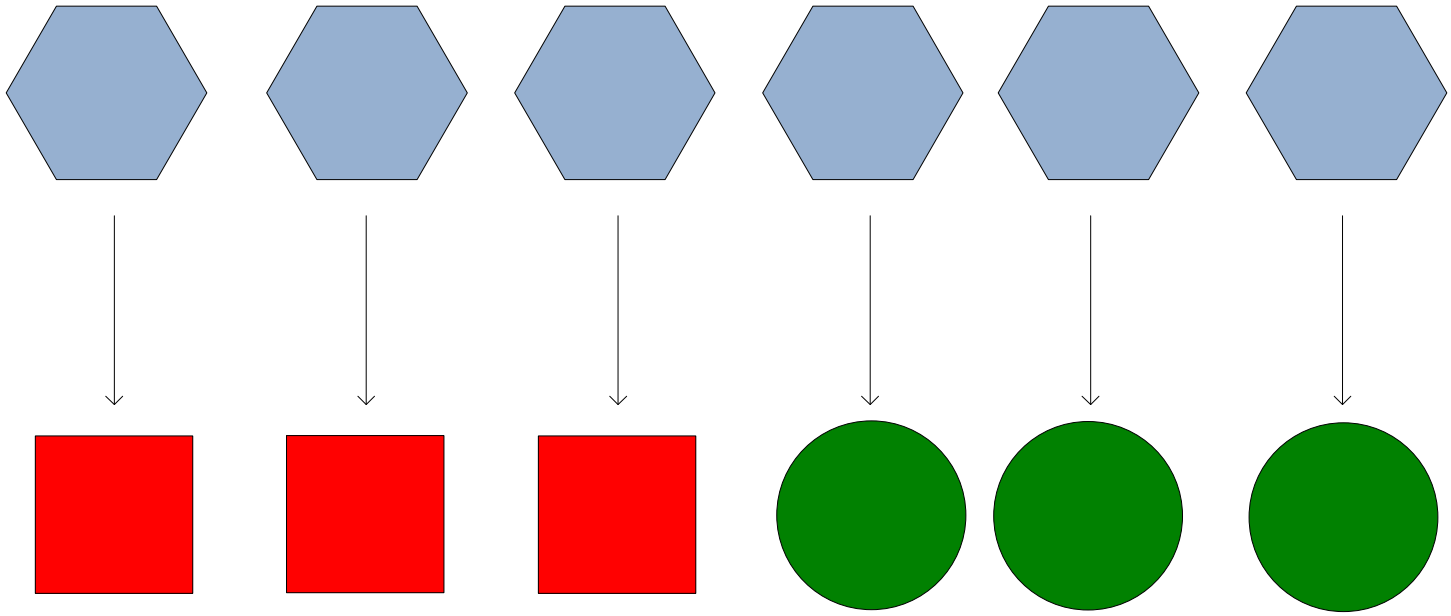
  - `reduce (out_key, intermediate_value list) ->`
    `out_value list`

map

- Records from the data source (lines out of files, rows of a database, etc) are fed into the map function as key*value pairs: e.g., (filename, line).
- map() produces one or more *intermediate* values along with an output key from the input.

map

```
map  (in_key, in_value) ->
   (out_key, intermediate_value) list
```

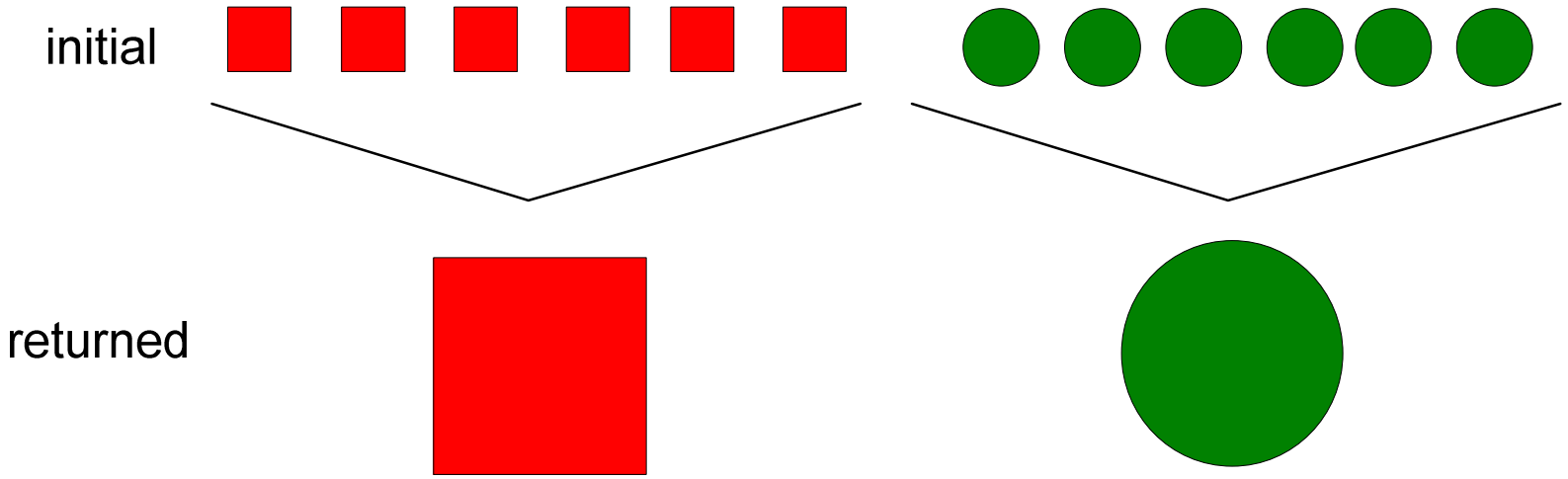


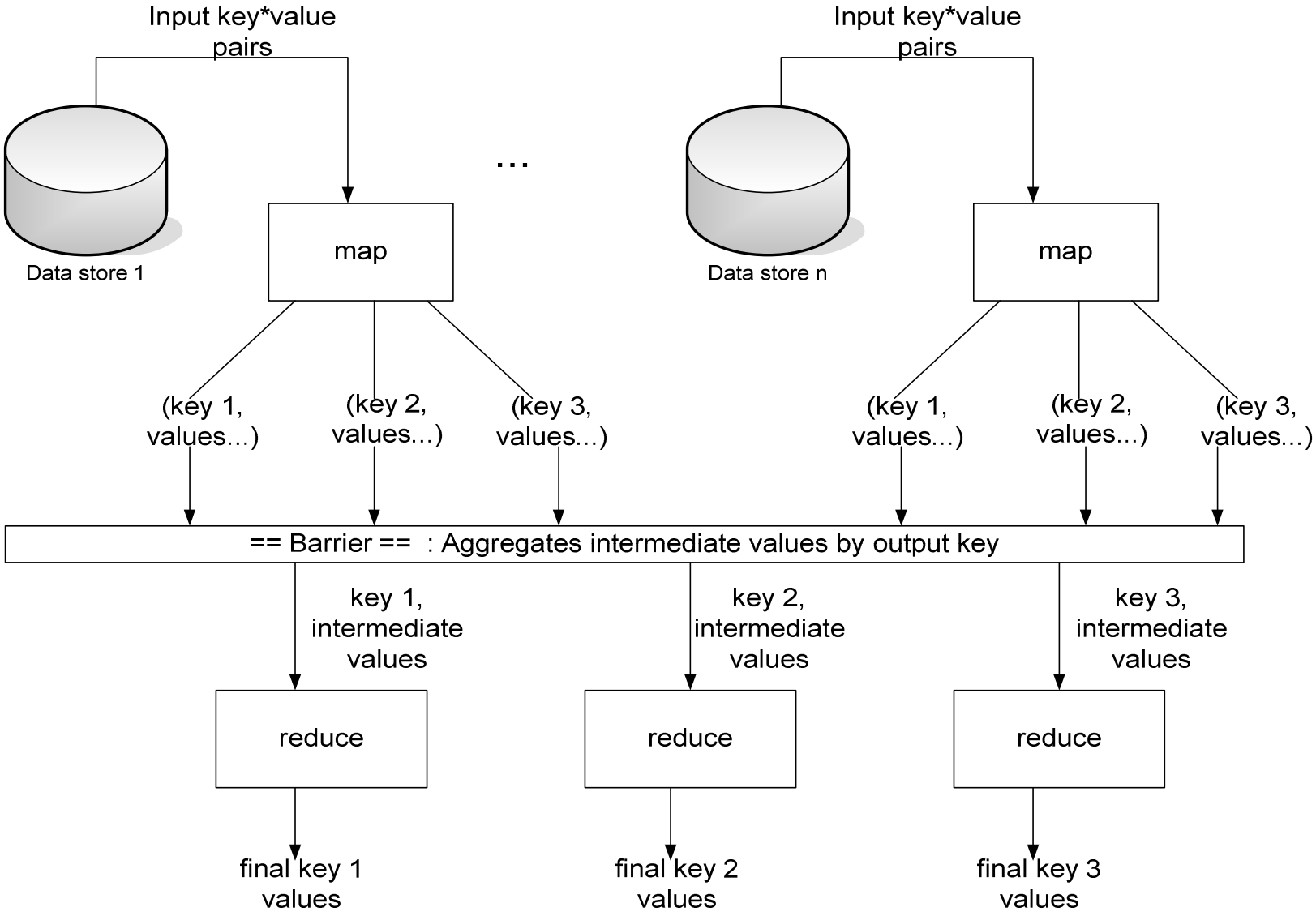
reduce

- After the map phase is over, all the intermediate values for a given output key are combined together into a list
- reduce() combines those intermediate values into one or more *final values* for that same output key
- (in practice, usually only one final value per key)

Reduce

```
reduce (out_key, intermediate_value list) ->
          out_value list
```




Input key*value pairs
Input key*value pairs
Data store 1
Data store n
map
map
(key 1, values...)
(key 2, values...)
(key 3, values...)
(key 1, values...)
(key 2, values...)
(key 3, values...)
== Barrier == : Aggregates intermediate values by output key
key 1, intermediate values
key 2, intermediate values
key 3, intermediate values
reduce
reduce
reduce
final key 1 values
final key 2 values
final key 3 values

Parallelism

- map() functions run in parallel, creating different intermediate values from different input data sets
- reduce() functions also run in parallel, each working on a different output key
- All values are processed *independently*
- Bottleneck: reduce phase can’t start until map phase is completely finished.

Example: Count word occurrences

```
map(String input_key, String input_value):
  // input_key: document name
  // input_value: document contents
  for each word w in input_value:
    EmitIntermediate(w, 1);

reduce(String output_key, Iterator<int>
  intermediate_values):
  // output_key: a word
  // output_values: a list of counts
  int result = 0;
  for each v in intermediate_values:
    result += v;
 Emit(result);
```

Example vs. Actual Source Code

- Example is written in pseudo-code
- Actual implementation is in C++, using a MapReduce library
- Bindings for Python and Java exist via interfaces
- True code is somewhat more involved (defines how the input key/values are divided up and accessed, etc.)

Locality

- Master program divvies up tasks based on location of data: tries to have map() tasks on same machine as physical file data, or at least same rack
- map() task inputs are divided into 64 MB blocks: same size as Google File System chunks

Fault Tolerance

- Master detects worker failures
  - Re-executes completed & in-progress map() tasks
  - Re-executes in-progress reduce() tasks
- Master notices particular input key/values cause crashes in map(), and skips those values on re-execution.
  - Effect: Can work around bugs in third-party libraries!

Optimizations

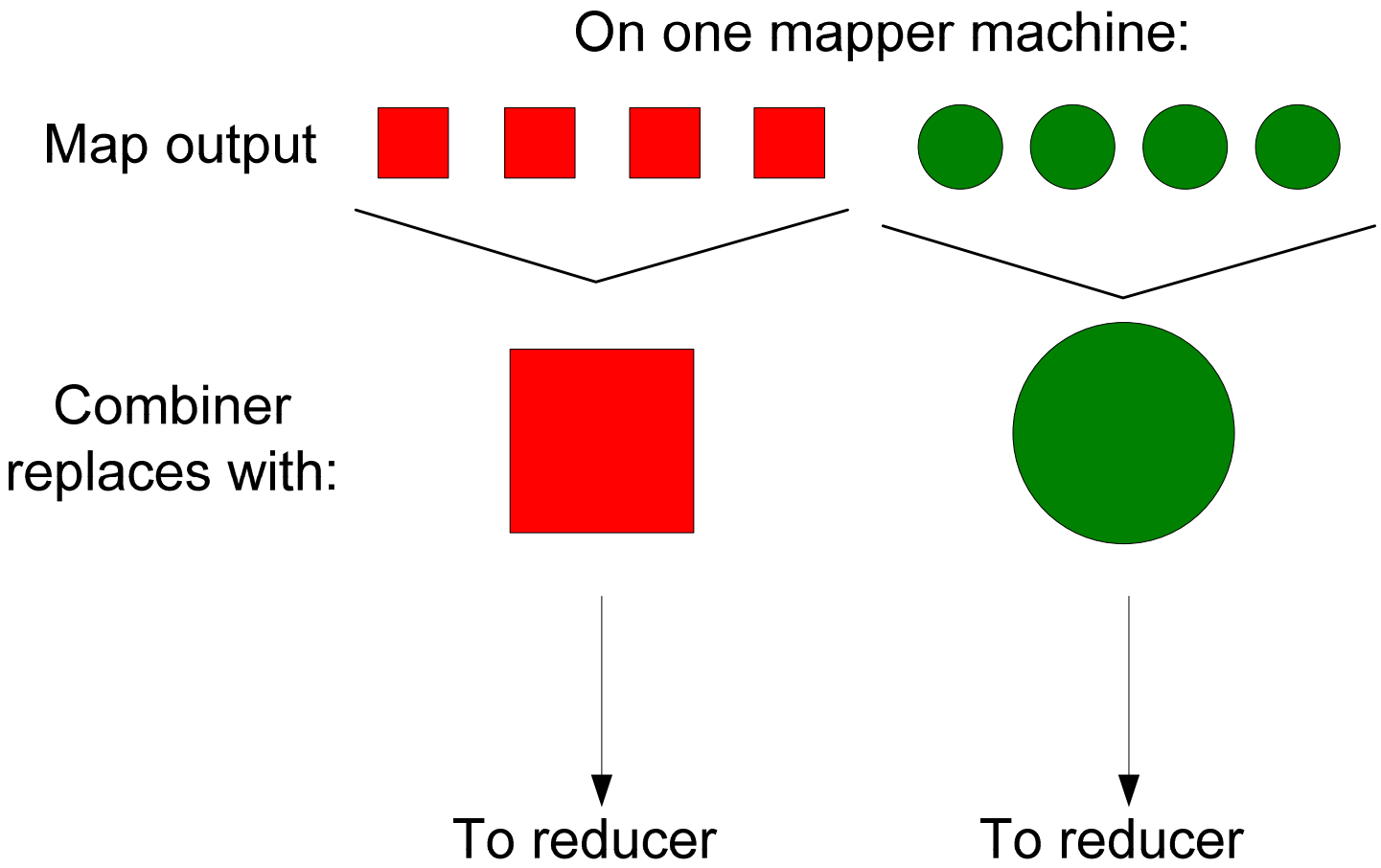
- No reduce can start until map is complete:
  - A single slow disk controller can rate-limit the whole process
- Master redundantly executes “slow-moving” map tasks; uses results of first copy to finish

Why is it safe to redundantly execute map tasks? Wouldn’t this mess up the total computation?

Combining Phase

- Run on mapper nodes after map phase
- “Mini-reduce,” only on local map output
- Used to save bandwidth before sending data to full reducer
- Reducer can be combiner if commutative & associative

Combiner, graphically



Word Count Example redux

```
map(String input_key, String input_value):
  // input_key: document name
  // input_value: document contents
  for each word w in input_value:
    EmitIntermediate(w, 1);

reduce(String output_key, Iterator<int>
  intermediate_values):
  // output_key: a word
  // output_values: a list of counts
  int result = 0;
  for each v in intermediate_values:
    result += v;
 Emit(result);
```

Distributed “Tail Recursion”

- MapReduce doesn’t make infinite scalability automatic.
- Is word count infinitely scalable? Why (not)?

What About This?

```
UniqueValuesReducer(K key, iter<V> values) {
  Set<V> seen = new HashSet<V>();
  for (V val : values) {
    if (!seen.contains(val)) {
      seen.put(val);
      emit (key, val);
    }
  }
}
```

A Scalable Implementation?

A Scalable Implementation

```
KeyifyMapper(K key, V val) {
  emit ((key, val), 1);
}

IgnoreValuesCombiner(K key, iter<V> values) {
  emit (key, 1);
}

UnkeyifyReducer(K key, iter<V> values) {
  let (k', v') = key;
  emit (k', v');
}
```

MapReduce Conclusions

- MapReduce has proven to be a useful abstraction
- Greatly simplifies large-scale computations at Google
- Functional programming paradigm can be applied to large-scale applications
- Fun to use: focus on problem, let library deal w/ messy details